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Fuzzy stochastic risk-based decision analysis with the mobile offshore base as a case study

Andrew Nyakaana Blair[a,*], Bilal M. Ayyub[a], William J. Bender[b]

[a]Center for Technology and Systems Management, Department of Civil and Environmental Engineering, University of Maryland, College Park, MD 20742, USA

[b]Central Washington University, 400 E 8th Avenue, Ellensburg, WA 98928, USA

Abstract

The Office of Naval Research in a feasibility study of a mobile offshore base (MOB) has proposed several concepts for very large ocean structures and will make risk informed assessments of alternative concepts. Using the MOB as a case study, this paper provides methodology for fuzzy-stochastic cost and schedule risk-based decision analysis of alternative MOB hull construction concepts. The uncertainty intrinsic in a system influences requisite risk-based decision analysis methodology. Probabilistic, ambiguous, or aleatory uncertainty entails stochastic methods. Cognitive, vague, or epistemic uncertainty requires fuzzy sets and logic. Simulation is used to overcome difficulty, or known intractability, associated with mathematical formulation of analytical models of complex engineering systems. This paper provides generalized fuzzy-stochastic risk-based decision analysis methodology and demonstrates fuzzy set quantification of MOB subjective information. Fuzzy-Bayesian updating of the state-of-knowledge of MOB cost and schedule information as it is piecewise accumulated is also discussed.

Keywords: Construction; Cost; Decision; Fuzzy; Risk; Schedule; Simulation; Stochastic; System; Uncertainty

1. Introduction

1.1. Overview

Risk management decisions are among the most conceptually difficult ones faced by managers [1]. Engineering decisions involving risk require decision models with

* Correspondence address. 5415 67th Avenue, Riverdale, MD 20737, USA. Tel.: + 1-301-925-443; fax: + 1-301-925-321.

E-mail address: ablair@eos.hitc.com (A.N. Blair).

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systematic frameworks to consider pertinent facets of decision problems and appropriate modeling, analysis, and assessment.

Several very large ocean structures have been proposed as part of the Office of Naval Research feasibility study of a mobile offshore base (MOB). The MOB platform is about 1609 m (1 mile) × 122 m (400 ft), which is unprecedented in size and operations compared to any floating structure to date. This paper uses MOB hull construction as a case study to demonstrate risk-based decision analysis methodology.

1.2. Objectives

The objectives of this paper are to provide methodology for fuzzy-stochastic risk-based decision analysis of alternative MOB hull construction concepts and to demonstrate fuzzy set quantification of MOB subjective information. A further objective is to discuss fuzzy-Bayesian updating of the state-of-knowledge of MOB cost and schedule information as it is piecewise accumulated.

2. Risk analysis

2.1. Definition of risk

The concept of risk is used to assess and evaluate uncertainties associated with an event. Risk can be defined as the potential for loss as a result of a system failure. Risk can be measured as a pair of the probability of occurrence of an event, and the outcomes or consequences associated with the event's occurrence. This pairing is not a mathematical operation, a scalar or vector quantity, but a matching of an event's probability of occurrence with the expected consequence.

2.2. Uncertainty modeling and analysis

2.2.1. Need for uncertainty treatment

A kernel element of risk is uncertainty represented by plural outcomes and their future likelihoods [2]. There has been a paradigm shift in science concerning the treatment of uncertainty. Not only is this considered from the statistical treatment of ambiguity but also the treatment of vagueness with fuzzy sets and logic. Vagueness is often encountered in linguistic expressions that do not crisply place a given subject matter in one class and require fuzzy sets.

2.2.2. Fuzzy sets and logic

A fuzzy set is a collection of items, with a confidence attached to each item representing the confidence with which the item belongs to the set. Fuzzy sets define classes of components with a continuum of grades of membership characterized by a membership (characteristic) function that assigns grades of membership from 0 to 1 (see Zadeh [3]).

Fuzzy logic is the concept of fuzzy sets incorporated into the framework of multivalued logic. Fuzzy logic provides a means of performing linguistic computations.

One of the basic ideas of fuzzy logic is that any statement employed in reasoning will have a corresponding confidence level. Fuzzy logic provides rules for the truth of complex statements. The confidence in a statement involving AND is the minimum of the confidences in the individual statements which make up the complex statement. If the complex statement involves OR, the confidence in the complex statement is the maximum of the confidences in the individual statements.

2.2.3. *Treatment of uncertainty*

A review of the literature finds a variety of treatments of uncertainty. Uncertainties can be classified into two broad categories, namely: probabilistic and cognitive [4]. Others generally classify uncertainties concerning engineering systems as ambiguity and vagueness [5]. These are also referred to as aleatory and epistemic uncertainties, respectively [6].

Uncertainty can be attributed to vagueness where there are ill-defined boundaries and ambiguity where there are several choices for a given situation [7]. Ayyub and Chao [8] recognize the following methods for cognitive and noncognitive types of uncertainty in structural and reliability analyses:

1. Deterministic analysis for cases without uncertainty in basic variables,
2. Stochastic analysis for cases with noncognitive type of uncertainty,
3. Fuzzy analysis for cases with cognitive type of uncertainty,
4. Fuzzy-stochastic analysis for cases with both cognitive and non-cognitive types of uncertainty.

In the above, 4 can be developed by combining 2 and 3. The MOB has hull construction activities whose durations and costs can be analyzed as deterministic, stochastic, fuzzy, or fuzzy stochastic and these methods of uncertainty analysis are applicable.

3. Fuzzy-stochastic risk-based decision analysis methodology

3.1. *Overview of methodology*

The methodology for risk-based decision analysis used in this paper is depicted in Fig. 1 (see [9]). Fig. 1 shows a generalized methodology starting with the abstraction from a real world complex system of a problem and system definition. A complete model for risk-based decision analysis is generally composed of a number of modules. Each module covers specific aspects of the system requiring analysis. Each aspect of the system is modeled using one of the following:

1. A deterministic module,
2. A stochastic module,
3. A fuzzy module,
4. A fuzzy - stochastic module.

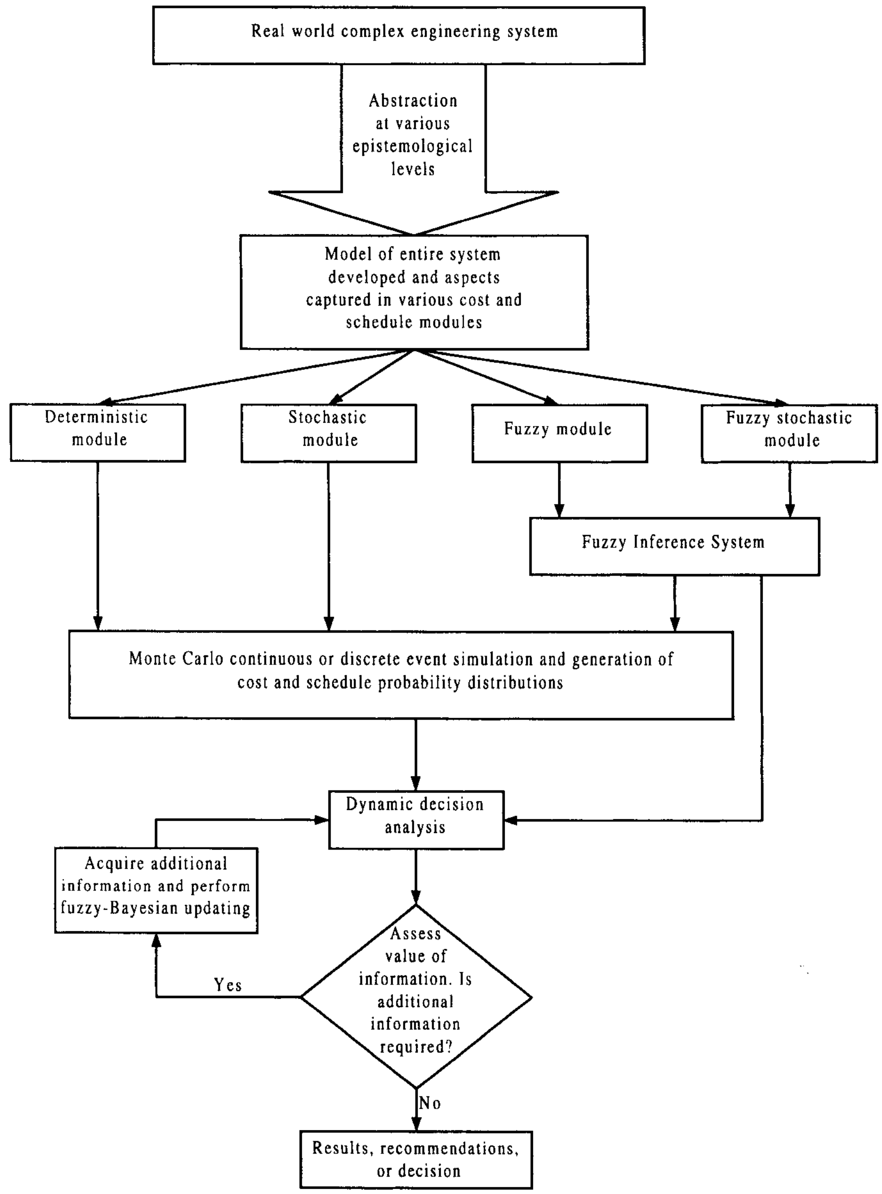

Fig. 1. Generalized methodology for fuzzy-stochastic risk-based decision analysis of cost and schedule of complex engineering systems.

The deterministic module models the aspects of the system that do not contain any probabilistic (i.e. random) components. The stochastic module models aspects of the system that have at least one random input component.

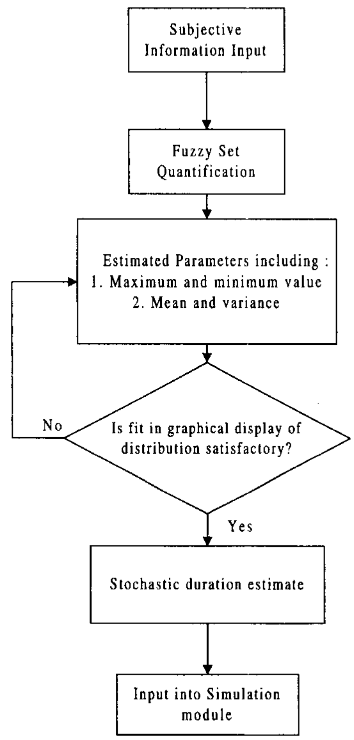

Fig. 2. Fuzzy-stochastic module.

The fuzzy module models aspects of the system that can be abstracted using fuzzy sets and logic. Quantification of subjective information by a fuzzy inference system using fuzzy sets involves variable definition, rule composition, translation, and execution, in that order [9]. In a fuzzy inference system, a fuzzy inference algorithm puts together elements of the fuzzy IF-THEN structure. These elements include fuzzy variables, membership functions, fuzzy rules, implication process, and decomposition [10].

The fuzzy-stochastic module combines the functions of the fuzzy and the stochastic modules. This module models components of the system that have at least one random variable and are fuzzy. The fuzzy-stochastic module is used when historical data is not available to categorize the underlying statistical distribution. The distribution categorization is based on subjective information provided by an 'expert.' This is done fuzzy stochastically following the steps below depicted in Fig. 2 [11].

1. Collect and input subjective information,
2. Quantify subjective information using fuzzy sets,
3. Estimate various parameters of distributions, including maximum and minimum values, and the mean and variances of the parameters,

4. Examine a graphical display of fitted distributions. The fitted distribution is affected by selection and membership values of the linguistic variables. If the fit is unsatisfactory, update estimated parameters,
5. From a satisfactory fit obtain a stochastic estimate of the duration,
6. Input results into the simulation module.

The results of the above modules are input into the simulation module where Monte Carlo simulation is performed. Linguistic variables are translated into mathematical measures by fuzzy sets and systems theory and conventional procedures like the program evaluation and review technique (PERT) are used [12]. The simulation module uses updated probabilistic input and application of the following steps results in risk estimates:

1. The critical path method (CPM) is performed on a project to identify critical and near critical paths,
2. Critical and near critical paths are modeled using PERT or graphical evaluation and review technique (GERT) procedures,
3. Continuous or discrete event simulations are run. The number of simulations to meet accuracy and stability requirements is determined statistically,
4. Risk-based decision analysis is performed on simulation results to give fuzzy-stochastic risk assessment.

A decision model is fed both outputs of the fuzzy logic inference system and Monte Carlo simulation. Sensitivity analysis is performed on the decision analysis results. The value of acquisition of any additional information can be assessed using fuzzy-Bayesian methods. Where additional information is acquired, fuzzy-Bayesian updating is used to up-date information and revise the results of the risk-based decision analysis.

3.2. *Risk-based decision analysis*

Engineering decisions involving risk need to be made using a systematic framework that considers many facets of a decision problem. This decision framework is called the decision model. The following elements of the decision model need to be defined in order to construct a decision model (see Ayyub and McCuen [13]): (1) objectives of decision analysis, (2) decision variables, (3) decision outcomes, and (4) associated probabilities and consequences. Systematic models in the form of decision trees can be used to examine information in decision making.

3.3. *Fuzzy-Bayesian updating and value of information*

Accurate estimates of risk-based decision analysis parameters require substantial amount of data. When observed data is limited, statistical estimates can be supplemented (or even superseded) by judgmental information using the Bayesian approach [14]. Its been shown that Bayes' theorem is an effective tool for updating prior probabilities [15]. Bayes' theorem gives the rule for updating belief in a hypothesis (i.e. its probability) given additional evidence, and background information (context). Bayes' theorem can be extended using the product rule from probability to multiple sequential updates and applied to the conditional probabilities obtained after decision analysis to update results as additional information is collected [9].

Since Bayes' theorem is an effective tool for updating prior probabilities and since subjective information can be analyzed using fuzzy set theory, the two theories can be combined, called fuzzy-Bayesian, to compute posterior probabilities (see [15]) and for multiple updates (see [9]).

3.3.1. The fuzzy-Bayesian method for multiple updates

Given event E_j, for $j = 1, 2 \ldots n$, where n is the number of mutually exclusive and collectively exhaustive events, and additional information A_i, for $i = 1, 2 \ldots m$, where m is the number of statistically independent multiple pieces of information, the fuzzy-Bayesian method for multiple updates can be represented as (see [9]):

$$P(E_j|A_1, A_2, \ldots, A_m) = \frac{P(E_j)\prod_{i=1}^{m}[\int_{x\in A_i}\mu_{A_i}(x)f_{x|E_j}(x)\,\mathrm{d}x]}{\prod_{i=1}^{m}[\sum_{k=1}^{n}[\int_{x\in A_i}\mu_{A_i}(x)f_{x|E_k}(x)\,\mathrm{d}x]P(B_k)]} \tag{1}$$

if continuous, and

$$P(E_j|A_1, A_2, \ldots, A_m) = \frac{P(E_j)\prod_{i=1}^{m}[\sum_{x\in A_i}\mu_{A_i}(x)P_{x|E_j}(x)]}{\prod_{i=1}^{m}[\sum_{k=1}{}^{n}[\sum_{x\in A_i}\mu_{A_i}(x)P_{x|B_k}(x)]P(B_k)]} \tag{2}$$

if discrete. This fuzzy-Bayesian approach can similarly be used to measure the value of additional information.

3.3.2. Value of information

The value of additional information (VI) can be measured by [16]:

$$VI = E(AI) - E(BI), \tag{3}$$

where $E(AI)$ is the utility or expected value of the optimal alternative in the analysis after acquisition of additional information and $E(BI)$ is utility or value before acquisition of additional information. If prior to obtaining information, VI exceeds the cost of acquisition of information then the additional information should not be acquired.

The value of the additional information however is bounded by a limit referred to as the 'value of perfect information' [16]. The value of perfect information (VPI) can be calculated using the equation:

$$VPI = E(PI) - E(BI), \tag{4}$$

where PI is perfect information, that is, information that has no probability of error. VPI represents the maximum cost a decision maker can allow for acquiring additional information.

4. MOB case study

4.1. MOB model building

Risk-based decision analysis of the MOB is performed using hierarchical modeling techniques to present discrete event simulations of potential construction concepts and scenarios (5 separate concepts and 2 different scenarios, see [17]). A number of software products are available for both discrete and continuous event simulations. One such software product, Extend™ by Imagine That, ® Inc., is used. Extend is a general-purpose graphically oriented, discrete event and continuous simulation software product.

The model layout for one of the concepts and scenarios, that of the rigid concept afloat scenario, is shown in Fig. 3. CPM network layouts, such as that in Fig. 3, are the basis for the models produced with Extend™. The heavy lines signify the critical path. For the MOB there are a total of 9 concept scenario combinations [17].

MOB construction simulation uses the central limit theorem, which implies that no matter what the underlying distribution is, the simulated schedule duration or cost mean will tend to a normal distribution as long as the assumption of the theorem of large number of input variables without a dominating distribution type are met. For each MOB concept and scenario combination, this theorem is applied to the critical path, for schedule duration, and to all activities, for cost [17]. In simulating total schedule duration, only activities on the critical path are considered while in simulating total cost, all activities are considered. Schedule duration is approximated by a normal distribution with a mean equal to the sum of the means and a variance equal to the sum of the variances of the activities on the critical path. Total cost is approximated by a normal distribution with a mean equal to the sum of the means and a variance equal to the sum of the variances of all activities in a given MOB concept and scenario combination. The probability associated with completing the

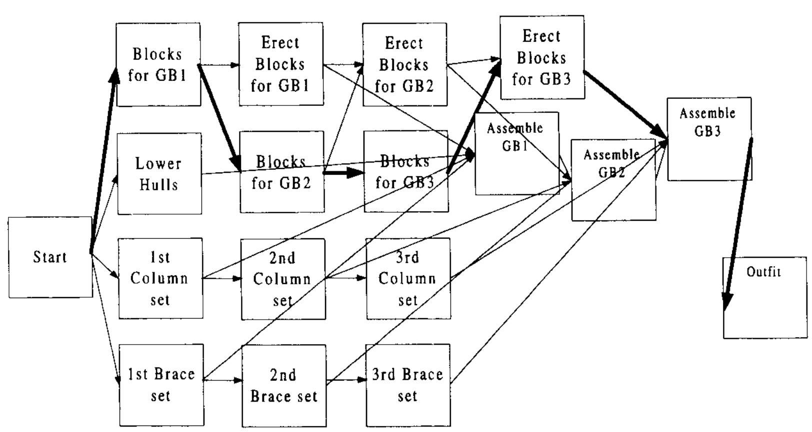

Fig. 3. Rigid concept afloat scenario model layout.

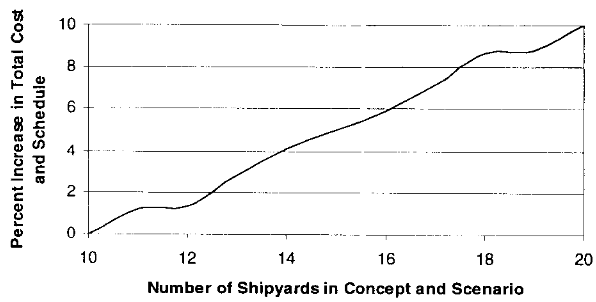

Fig. 4. Fuzzy assessment of construction management conditions.

project within certain time or cost limits can then be computed using standard normal distribution formulae.

4.2. Fuzzy assessment of construction management conditions

Construction management conditions impact a given concept cost and schedule due to the complexity and interdependence of integrating components from several facilities. The uncertainty involved is subjective and thus incorporated into simulation using fuzzy sets and logic.

Two variables are defined for this fuzzy analysis [9,17]. The input variable is the number of shipyards involved in a given concept and scenario which is a measure of the complexity involved. The output variable is the percentage increase in total cost and schedule.

Membership functions for the variables are formulated. Three triangular membership functions, small, medium, and large are defined per variable. The range of the number of shipyard input variable is set from 10 to 20. The range of the percent increase in total cost and schedule output variable is set from 0 to 10%. IF-THEN rules are composed for a fuzzy inference engine to map input variable to output variable. These rules are translated and executed with inputs for 10–20 shipyards. The results from this fuzzy analysis are given in Fig. 4 and are used in simulations. For example, there are 12 shipyards involved in the rigid afloat concept and scenario, thus the simulated results for cost and schedule are increased by 1.3% to account for construction management conditions.

4.3. Number of simulation cycle determination

MOB construction simulation requires determination of the number of simulation cycles that meet accuracy and stability requirements. To determine the accuracy of simulation results, the number of cycles necessary to achieve an acceptable error level in the estimate of a given MOB concept and scenario schedule duration and cost are computed from the results of an initial 50 cycle run. A standard 95% confidence level

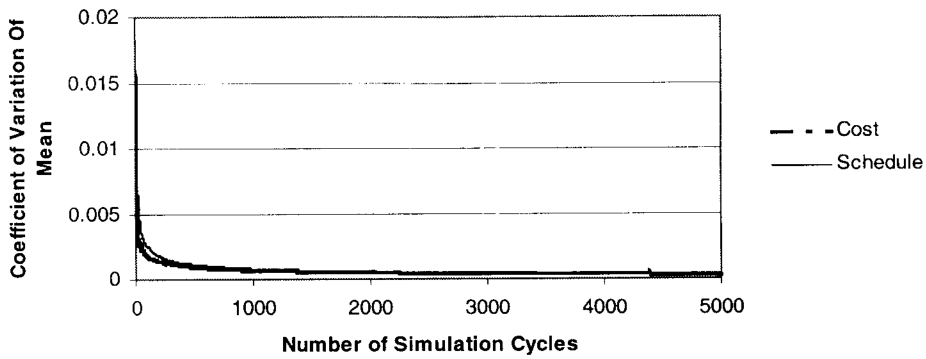

Fig. 5. Coefficient of variation of mean cost and schedule as a function of the number of simulation cycles.

is assumed. Use is made in the simulations of cost and schedule estimates that are preliminary with a precision in the 15% order of magnitude. In simulating based on this data, a simulation accuracy (e) equal to 1% of the cost and schedule of any given MOB concept and scenario module is specified which is one order of magnitude more than the precision of the input data and should improve results.

With a 95% confidence level and a specified accuracy (e), the minimum number of cycles (n) per simulation run are given by

$$n = \frac{\sigma^2}{e^2}(1.96)^2 \tag{5}$$

Simulations with 50 cycles are run for each concept and scenario combination and Eq. (5) is applied to determine the minimum number of simulations for assumed confidence levels and specified accuracy [17]. For example, for the rigid concept, the results are that a minimum of 47 and 15 cycles for schedule and cost, respectively, are required. Thus the minimum required cycles for both cost and schedule is 47.

Having found the minimum number of cycles required per simulation, the stability of the results from simulation to simulation are investigated. Convergence tests of the coefficient of variation of the mean are done to determine the number of cycles required to obtain stable results. The variation of coefficient of variation of the mean with number of cycles for the rigid concept afloat scenario is shown in Fig. 5. The variation of the mean of cost and schedule with number of cycles for the rigid concept afloat scenario are similarly reviewed and it is found that the simulation results stabilize after 2000 cycles [17]. After 2000 cycles no significant change in coefficient of variation of the mean or mean cost or schedule is obtained with increased number of simulation cycles. As such, 2000 cycles are simulated and the simulation results for all concept and scenario combinations are obtained and used in decision analysis [17].

5. Decision analysis

5.1. Objective of decision analysis

The main objectives of MOB construction are minimizing total cost, minimizing total schedule duration, optimizing total MOB length, minimizing labor and safety impact, and minimizing environmental impact. MOB construction thus involves multiple objective decision making. MOB objectives are stated in the same units, and weight factors are used to combine the objectives. This requires determination of objective weighting and utility for multiple objective decision making [9].

5.2. Objective weighting

The relative weighting shown in Fig. 6 are assigned to the various MOB objectives. In setting the relative weights given in Fig. 6, a three-step ranking procedure is used [16]. First, ordinal ranking is performed, whereby the 5 objectives are listed in decreasing order of importance. In Fig. 6, the objectives are ranked from left to right in decreasing order of importance. Next, the cardinal ranking of each of the objectives is established. In this step, the relative importance of each objective with respect to the other objectives is evaluated by assigning numerical weights to each of the objectives. Lastly, weights are normalized such that the sum of the weights is 100 as shown in Fig. 6. These weight factors can also be developed using decision techniques such as the analytic hierarchy process through pairwise comparisons of objectives and solving the resulting matrix of comparisons for its eigenvalues [18].

5.3. MOB objective utility functions

Taking into consideration the weighting factors given to the various objectives, utility functions are derived. The utility functions represent a decision makers preference for various possible outcomes over the entire range of possible future outcomes [9].

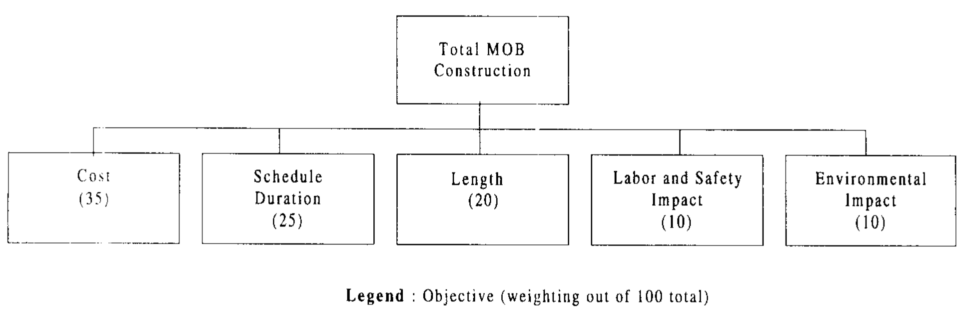

Fig. 6. Weighting factors for MOB objectives.

5.3.1. Cost utility

The MOB is a US Government funded venture and the Government can be assumed to be risk neutral. This is because the Government's subjective value of the next dollar of saving or expenditure is the same as the subjective value to the Government of the previous dollar of saving or expenditure. The utility function is therefore a straight line with the x-axis ranging from \$1500 million to \$6000 million representing the estimated range of MOB construction costs and the y-axis ranging from 0 to 35 utility units to conform to the weights given in Fig. 6. For a given cost x (in million \$), utility is given by

$$Utility = \begin{cases} 35, & x < 1500, \\ 35\left(1 - \left(\dfrac{x - 1500}{4500}\right)\right) & 1500 \leqslant x \leqslant 6000, \\ 0 & x > 6000. \end{cases} \tag{6}$$

5.3.2. Schedule utility

It is estimated that, given concepts currently under consideration, it is not possible to construct an entire MOB in less than 4 yr. As such, maximum utility is derived from a 4 yr schedule. It is also assumed that any schedule greater than 12 yr would have less than zero utility to the owner. Schedule utility between 12 and 4 yr is assumed to change proportionately. In this utility function, the x-axis ranges from 0 to 12 yr and the y-axis is shown from 0 to 25 utility units to conform with the weights given in Fig. 6. For a given total MOB schedule duration x (in years), utility is given by

$$Utility = \begin{cases} 25, & x < 4, \\ 25\left(1 - \left(\dfrac{x - 4}{8}\right)\right) & 4 \leqslant x \leqslant 12, \\ 0 & x > 12. \end{cases} \tag{7}$$

5.3.3. Length utility

To meet operational requirements, MOB concepts up to 1609 m (1 mile) in length are being considered. Various concepts have module designs such that the physical configuration of the total MOB as a combination of a given number of modules results in total MOB length that varies from concept to concept. In establishing length utility, it is assumed that for the envisaged operational requirements, a length less than 610 m (2000 ft) would have no utility while a MOB total length of 1524 m (5000 ft) or greater would have maximum utility. In this utility function, the x-axis varies from 610 m (2000 ft) to over 1524 m (5000 ft) while the y-axis is shown from 0 to 20 utility units to conform to the weights given in Fig. 6. For a given total MOB length x (in m), utility is given by

$$Utility = \begin{cases} 0, & x < 610, \\ \dfrac{10}{457}(x - 610) & 610 \leqslant x \leqslant 1524, \\ 20 & x > 1524. \end{cases} \tag{8}$$

5.3.4. Labor, safety and environmental impact utility

From an owner's perspective, a MOB that has acceptable labor and safety impact and that does not adversely impact the environment is required. As such, the owner has maximum utility for a MOB that meets these requirements and no utility for a MOB that does not. If the objective of labor, safety and environmental impact are acceptable, maximum utility is obtained. If unacceptable, zero utility is perceived. Therefore, a discrete assignment is used herein. For labor and safety impact and for environmental impact, the utility as a function of x (where x is either acceptable or unacceptable) is given by

$$Utility = \begin{cases} 10 & x = acceptable, \\ 0 & x = unacceptable. \end{cases} \tag{9}$$

5.4. Definition of decision variables

The decision variables are the feasible options or alternatives currently envisaged for the MOB. These variables include Concept, Scenario, Labor and Safety Impact, and Environmental Impact [17]. For the Concept variable possible values are Rigid, Hinged, Independent, Flexible, or Concrete and Steel. For the Scenario variable possible values are Afloat Assembly or Terrestrial Assembly. For the Labor and Safety Impact variable possible values are Acceptable or Unacceptable. And for the shipyard site Environmental Impact variable possible values are Manageable or Prohibitive.

5.5. Definition of decision outcomes, associated probabilities and consequences

5.5.1. Fuzzy assessment of labor, safety, and environmental impact

The uncertainty involved in assessing labor, safety, and environmental impacts is subjective and thus incorporated into simulation using fuzzy analysis. Two fuzzy inference models are set up [9,17]. One for labor and safety impact analysis and one for environmental impact analysis.

In labor and safety impact analysis, three variables are defined for fuzzy analysis. The input variables are expense and time required for a given concept and scenario which are indicators of the strain on the site labor market and possibility of safety hazards. The output variable is labor and safety impact acceptability.

In environmental impact analysis three variables are defined for fuzzy analysis. The input variables are size of the principle shipyard involved in lower hull construction in a given concept and scenario and the scenario itself which are measures of the requirements for site modification with resultant environmental impact. The output variable is an environmental impact rating

Membership functions for the variables are formulated. Triangular membership functions are defined and the range of the variables are set. For output variables, two membership functions are defined. The range of the impact ratings given by the output variables is set from 0 to 1. Rules, composed for the fuzzy inference engine to map input variable to output variable, are developed. Six rules are developed for both labor and safety impact analysis and five for environmental impact analysis. For example, one of the rules developed for environmental impact analysis is:

Rule 1: IF {Shipyard Size is tiny OR Shipyard Size is very small OR Shipyard Size is small} AND Concept is Terrestrial THEN Environmental Impact is prohibitive

5.5.2. Fuzzy translation and utility mapping

The rules are translated and executed and the possibility given by the fuzzy inference engine for the occurrence of a given output is obtained. This possibility represents a subjective degree of confidence in the truth of the proposition that a given outcome will occur. The possibility value is normalized and is used as a probability measure in the decision trees [9].

The cost and schedule results obtained from concept and scenario simulations are mapped to the respective utility function to obtain the utility of the results. The total lengths of the various MOB concepts are mapped to the length utility function to obtain the utility of each concepts total length [9,17]. The utilities are incorporated into decision trees.

5.6. Decision trees

Selected parts of the decision tree for the MOB are depicted in Figs. 7–9. The decision nodes are identified in the model using a square symbol and the chance nodes are identified with a circle symbol.

Only a portion of the decision tree required to represent the information for the MOB is shown in Figs. 7–9. The entire decision tree consists of Figs. 7, 5 figures similar to Fig. 8 (one for each concept) and 25 figures similar to Fig. 9 (one for each shipyard in each concept) [17].

Figs. 7–9 are used to illustrate how the total expected utility is computed. The expected branch utility is computed for the end of the right-most decision node in Fig. 9. At decision nodes, the branch with the highest utility is chosen while at chance nodes, the expected utility is computed.

For example, the total expected utility for the Ingalls shipyard, utilized for afloat assembly of the rigid concept is obtained as follows:

Length utility	= 7	(from Fig. 7)
Cost utility	= 33	(from Fig. 8)
Schedule utility	= 8	(from Fig. 8)

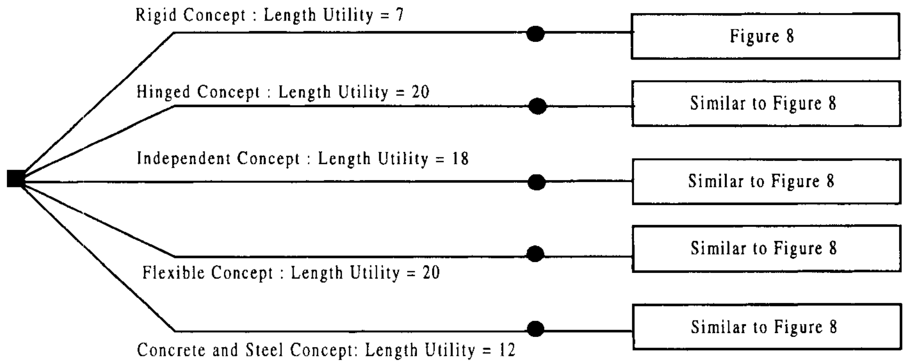

Fig. 7. Decision tree for MOB concept and scenario selection.

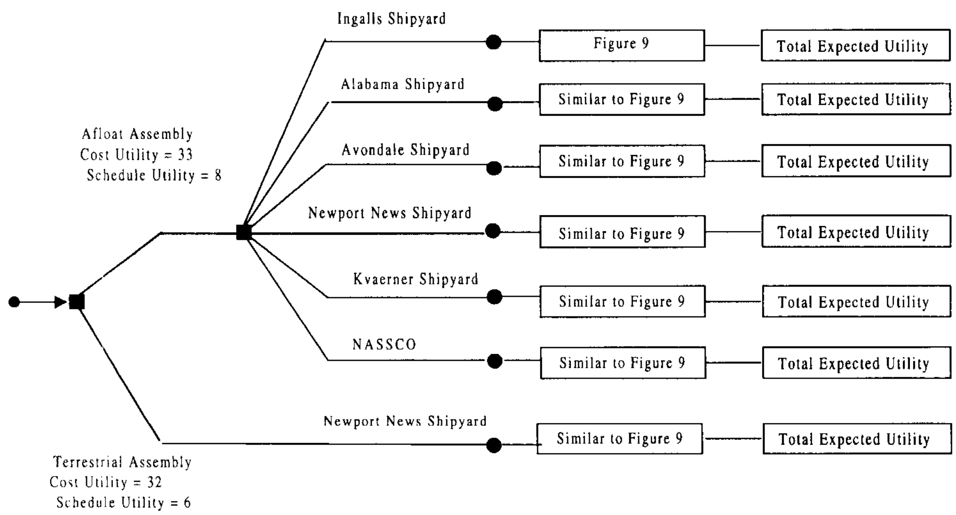

Fig. 8. Portion of decision tree for rigid concept scenario and shipyard selection.

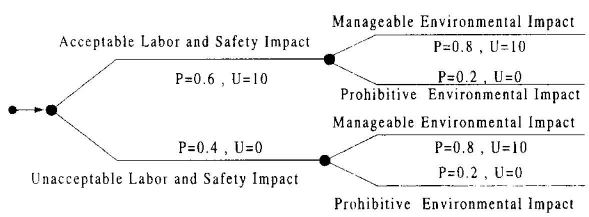

Fig. 9. Portion of decision tree for rigid concept labor, safety and environmental impact outcome for Ingalls shipyard.

Labor and safety impact utility	= 6	(from Fig. 9)
Environmental impact utility	= 8	(from Fig. 9)
Total expected branch utility	= 62	

This procedure is used to compute expected branch utilities for the entire MOB (see [9] and [17]).

5.7. Uncertainty considerations in MOB utility

The different kinds of uncertainty inherent in the utility values of the various MOB objectives are as follows:

1. The cost and schedule duration objective utilities have stochastic uncertainty as modeled by discrete event simulation,
2. Length is as designed and specified and its utility is assumed deterministic,
3. Labor and safety impact and environmental impact objectives are modeled using fuzzy inference and thus their utilities have inherent fuzzy uncertainty.

As such, the total MOB utility is a hybrid number with deterministic components, stochastic components, and fuzzy components. If required by a decision maker, this uncertainty can be analyzed by going beyond mean values and modeling the variability inherent in the total concept and scenario utility (see [9]). The expectation of the utility function U of x where x is random variable with a probability density function $f(x)$ is given by

$$E[U(x)] = \int_{-\infty}^{\infty} U(x) f(x)\,\mathrm{d}x \tag{10}$$

and the variance by

$$Var\,U(x) = E[U(x)^2] - E[U(x)]^2. \tag{11}$$

Solutions to Eqs. (10) and (11) can be determined analytically or by simulation to give the utility variability [9].

5.8. Sensitivity analysis

The utility values for the various concepts and scenarios as obtained from the decision trees are based on various parameters and assumptions which are subject to change. One such parameter is the total MOB length necessary to meet operational requirements.

It is assumed that a MOB length of 1524 m (5000 ft) or greater has maximum length utility. A sensitivity analysis is done to examine the change in concept and scenario total utility with a different MOB overall length requirement. Due to changes in scope of MOB operational requirements, a total MOB length of 1829 m (6000 ft) or greater may be appropriate. Under this scenario, in establishing length utility, it is assumed

Table 1
Sensitivity analysis results

Concept	Scenario	Utility with total required MOB length of 1524 m (5000 ft)	Utility with total required MOB length of 1829 m (6000 ft)
Rigid	Afloat assembly	72	43
	Terrestrial assembly	69	43
Hinged	Afloat assembly	60	59
	Terrestrial assembly	62	61
Independent	Afloat assembly	66	62
Flexible Bridge	Afloat assembly	62	49
	Terrestrial assembly	63	51
Steel & Concrete	Afloat assembly	65	65
	Terrestrial assembly	48	46

that for the envisaged operational requirements, a length less than 914 m (3000 ft) would have no utility while a MOB total length of 1829 m (6000 ft) or greater would have maximum utility.

In the resultant straight-line utility function, the x-axis varies from 914 m (3000 ft) to over 1829 m (6000 ft) while the y-axis is shown from 0 to 20 utility units to conform to the weights given in Fig. 6. A sensitivity analysis using this utility function for a required entire MOB length of 1829 m (6000 ft) yields the results given in Table 1 [17]. This analysis is based on mean simulation results. Table 1 shows that the rigid afloat concept has the greatest utility when the required MOB length is 1524 m (5000 ft) while the steel and concrete afloat assembly has the greatest utility when the required MOB length is 1829 m (6000 ft). The independent, steel and concrete afloat assembly and hinged terrestrial assembly concept and scenario total utilities are found to be insensitive to required length variation within the 1524 m to 1829 m (5000–6000 ft) range.

The total utility consists of a weighted sum of the utility of the objectives of cost, schedule duration, total MOB length, labor and safety impact, and environmental impact. Total required MOB length is obtained for each concept by increasing the number of modules required for an entire MOB such that a total length of 1829 m (6000 ft) or more is obtained. The physical configuration of the individual modules of each MOB concept remain the same. As a result, all concepts obtain maximum length utility. The utility for labor and safety impact, and environmental impact is dependent on individual module length and not entire MOB length. As such, these utilities are invariant to change in total required MOB length.

The main cause of total utility variation with total MOB length is cost and schedule change. The independent, steel and concrete, and hinged concepts are relatively insensitive to required length variation between 1524 and 1829 m (5000 and 6000 ft) because these concepts require only one additional module in order to achieve or exceed the increased length requirements. The modules in the rigid concept are the smallest at 152 m (500 ft) long and the original concept is only 914 m (3000 ft) and thus an increase to 1829 m (6000 ft) doubles the number of modules and drastically reduces cost and schedule utility. The flexible bridge concept is sensitive to required length variation because any additional module necessitates an additional bridge.

In general, the variation from shipyard to shipyard and from concept to concept is not large. The highest ranked and the next highest ranked concept, scenario, and shipyard have less than a 5% difference in utilities. This is an indication of the need for further investigation to obtain more discerning results. Acquisition of further information has to balance investigation costs with the value of sample information. The value of the additional information however is bounded by a limit referred to as the value of perfect information as previously described.

When additional information is obtained, the probabilities used in the decision trees obtained from simulation and fuzzy analysis can serve as prior probabilities. These probabilities can then be updated using Bayes' theorem to obtain posterior probabilities. In cases where some of the probabilities are fuzzy, fuzzy-Bayesian updating can be applied (see [9]).

5.9. Applicability of methodology

Many systems require quantification of subjective information and treatment of uncertainty. This paper provides a generalized methodology for risk analysis of cost and schedule of complex engineering systems. The methodology includes simulation of the cost and schedule of deterministic, stochastic, fuzzy, and fuzzy stochastic activities in PERT or GERT networks.

Decision analysis methodology is provided that combines the necessary facets of decision making. Fuzzy-Bayesian methodology is provided in which fuzzy set theory is used to facilitate the quantification of qualitative information and the incorporation of subjective parameters in probability theory. Bayes' theorem can be used to update prior probabilities and combined with fuzzy theory in a decision framework involving decision trees.

The methodology given is validated by application to a selected case study. The methodology provided is general in that it handles all kinds of uncertainty and the same concepts can be applied to areas other than the case study given.

6. Summary and conclusions

Methodology is provided in this paper that includes discrete event simulation of CPM networks to provide information for risk-based decision analysis. A fuzzy logic inference system is used to capture both quantitative and subjective information in the form of numerical and linguistic data entry enabling use of approximate MOB data. This information is used in discrete event simulation networks to perform fuzzy-stochastic modeling. A decision tree is fed both outputs of the fuzzy logic inference system and the network simulation. Sensitivity analysis is performed on the decision analysis results. The application of Bayes' theorem to up-date information obtained from the results of the risk-based decision analysis is discussed.

The decision analysis process for the MOB combines the potential effects of cost, schedule, length, labor, safety, and environmental impact to produce utilities to guide decision makers. The sensitivity analysis results demonstrate the effect on utility of specified changes in selected inputs. Other variations may be examined as required by the decision maker. For example the decision-maker may require that the results of the decision model be analyzed for sensitivity to variation in choice of cost and schedule probability of occurrence and objective weighting. Not only could the factors given be varied but also additional factors can be taken into account. For instance, the decision maker could request inclusion of an additional factor such as shipyard availability since the larger shipyards have greater utility but may not be available.

At the decision makers discretion, further investigation may be done to obtain more discerning results. Acquisition of further information has to balance investigation costs with the value of additional information. Any new information can be used to update risk-based decision analysis using Bayesian or fuzzy-Bayesian updating.

Methodologies for the implementation of fuzzy-stochastic risk-based analysis of alternative MOB hull construction concepts are given. Fuzzy set quantification of MOB subjective information is demonstrated. Fuzzy-Bayesian updating of the state-of-knowledge of MOB cost and schedule information as it is piecewise accumulated is discussed. A generalized methodology for risk analysis of cost and schedule networks with fuzzy and stochastic uncertainties is provided to cover deterministic, stochastic, fuzzy and fuzzy-stochastic activities connected in PERT or GERT networks.

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